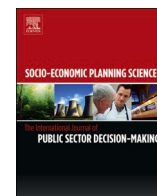




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Scientific planning of urban cordon sanitaire for desired queuing time

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ABSTRACT

The outbreak of the COVID-19 pandemic disrupted our normal life. Many cities enforced a cordon sanitaire as a countermeasure to protect densely inhabited areas. Travelers can only cross the cordon after being checked. To minimize the waiting time in the queue, this paper proposes a method to determine the scientific planning of urban cordon sanitaire for desired queuing time, which is a significant problem that has not been explored. A novel two-stage optimization model is proposed where the first stage is the transportation system equilibrium problem to predict traffic inflow, and the second stage is the queuing network design problem to determine the allocation of test stations. This method aims to minimize the total health infrastructure investment for the desired maximum queuing time. Note that queuing theory is used to represent the queuing phenomenon at each urban entrance. A heuristic algorithm is designed to solve the proposed model where the Method of Successive Averages (MSA) is adopted for the first stage, and the Genetic Algorithm (GA) with elite strategy is adopted for the second stage. An experimental study with sensitivity analysis is conducted to demonstrate the effectiveness of the proposed methods. The results show that the methods can find a good heuristic optimal solution. This research is helpful for policymakers to determine the optimal investment and planning of cordon sanitaire for disease prevention and control, as well as other criminal activities such as drunk driving, terrorists, and smuggling.

1. Introduction

The COVID-19 pandemic is an ongoing global pandemic of coronavirus disease. It has disrupted our normal life and collapsed global financial markets [1]. Local authorities worldwide have responded by implementing travel restrictions, lockdowns, workplace hazard controls, and facility closures to control the rapid spread of the pandemic. Many places have also worked to increase testing capacity and trace contacts of infected people. Particularly, a cordon sanitaire was set up on January 23, 2020, to control travel into and out of Wuhan, a city with over 11 million people. Then similar measures were extended to many other cities. Formally, a cordon sanitaire restricts people's movements into or out of a defined geographic area, such as a community, city, or region, to control diseases. Only qualified travelers, after testing, can cross the cordon.

Although the enforced cordon sanitaire has been demonstrated to be an effective way to prevent or slow down the infectious virus from spreading into a protected area, many problems are associated with it. Notably, the queue length can be too long, and the waiting cost can be too high at the cordon sanitaire (Fig. 1). Therefore, there is an urgent

need to optimize the queuing system to improve the service level of testing. This paper proposes a method to deploy test stations along the cordon sanitaire to minimize the waiting time. The goal is to strike a balance between the cost of offering test stations and the cost of waiting time endured by travelers. It helps control and prevent epidemics and other criminal activities such as drunk driving, terrorists, and smuggling.

With the outbreak of COVID-19, the optimal investment of cordon sanitaire, including the location and the number of test stations, is a new problem that has not been investigated yet. However, a similar problem, cordon pricing, has been explored extensively. Cordon pricing is a toll paid by private vehicles to enter a restricted area, usually within a city center, as part of a travel demand management strategy to mitigate traffic congestion. It has been successfully implemented in several cities, such as London, Stockholm, and Singapore. Earlier studies have demonstrated that the performance of cordon schemes is critically dependent on toll locations and toll levels [2,3]. The achievements in cordon pricing research could inspire the study of cordon sanitaire.

The cordon pricing and cordon sanitaire have similarities and differences. They both operate at the entry links around a restricted area.

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Fig. 1. Vehicle queue for COVID-19 testing (Source: Mario Tama/Getty Images).

The difference is that cordon pricing aims to determine the optimal toll levels, while cordon sanitaire seeks to determine the optimal number of test stations. In general, queue length on a road network is highly dependent on toll locations and toll levels. It is traditionally assumed that, in cordon pricing, the policymaker sets tolls to maximize social welfare, which is defined as total benefits minus total costs according to the Marshallian measure. However, recent researches tend to concern sustainability which can be defined in terms of equity and environment. If some travelers' service levels deteriorate significantly, the cordon schemes could be infeasible. Abulibdeh et al. [4] used origin-destination data to assess the vertical equity effects of a hypothetical cordon pricing scheme in Canada's largest city. Souche et al. [5] and Souche et al. [6] simulated the impact of cordon pricing on equities using both social and spatial indicators (Gini, Theil, and Atkinson indices) to make a city sustainable. They concluded that introducing a toll would increase inequalities, and it was crucial to investigate any changes among different categories of network users. Camporeale et al. [7] explored the equity effects using the Theil equity index, taking into account an elastic demand associated with the cordon pricing strategy.

In summary, a bilevel optimization model with an equity constraint is usually developed to reduce inequities. Besides equity issues, environmental issues are also considered for sustainable development. Gühnemann et al. [8] analyzed the application of cordon pricing to reduce local air pollution and maximize social welfare. Li et al. [9] focused on an environmental-friendly cordon pricing design problem, where an acceptable road network performance was promised.

The cordon pricing problem is still an exciting topic in transportation research, and there are several directions for future research. First, a logsum-based social welfare computation before and after a change in the travel environment could be used as an essential policy evaluation measure [10,11]. Provided that logit choice models are widely adopted to simulate a consumer's response to a policy, consumer surplus can be easily computed using the model's logsum. Therefore, utilizing a logsum-based objective function in designing a cordon pricing scheme would likely be feasible for most planning agencies. Second, stochastic user equilibrium with elastic demand is used to represent route choice [12–14]. Unsurprisingly, the stochastic user equilibrium could be more realistic than the deterministic user equilibrium. Third, mixed traffic flow is considered in a cordon tolling model, including motorcycle and automobile trips [15,16]. Last, combination models are proposed to address cordon pricing and other issues, such as road capacity choice [17] and land-use regulation [18].

The contributions of this paper lie in three aspects, given the intrinsic differences between cordon sanitaire and cordon pricing. Firstly, the design of cordon sanitaire is a new problem that has never been explored. It is an effective measure to fight the COVID-19 pandemic. However, the COVID-19 pandemic would not be the last pandemic. It is beneficial to make an effort, and we must prepare well for future challenges. Secondly, the queuing theory is used to describe the

phenomenon of waiting at the sanitary cordon, but it is rarely applied to the pricing cordon. With Electronic Toll Collection (ETC) being widely implemented, there is no need for the inflow vehicles to stop to pay tolls. Thirdly, a two-stage optimization model is proposed for desired queuing time. An efficient and operable heuristic solution method is proposed according to the two-stage decision structure, which is adaptable for similar lockdown problems. Several findings and managerial insights are provided based on experimental studies.

The structure of this paper is organized as follows in order to study the urban cordon sanitaire for desired queuing time. Section 2 proposes a two-stage model, where the first stage is traffic inflow prediction, and the second stage is queuing network design. Section 3 proposes an explicit algorithm, where the Method of Successive Averages (MSA) is adopted for the first stage, and the Genetic Algorithm (GA) with elite strategy is adopted for the second stage. Section 4 demonstrates the effectiveness of the model and algorithm through an experimental study. Section 5 concludes this paper.

2. Methodology

This paper proposes a method and an algorithm to design a queuing network in terms of parallel test stations at city entrance links. Since the queuing network optimization is based on traffic inflow prediction, a two-stage model is proposed. The first stage is traffic inflow prediction, and the second stage is queuing network optimization. Fig. 2 shows the model's conceptual framework. The first stage is a feedback procedure between trip distribution and traffic assignment. It is usually known as transportation system equilibrium. The detailed models are elaborated on in the following sections.

2.1. Stage 1: Traffic inflow prediction

The first stage model is a transportation system equilibrium that combines trip distribution and traffic assignment models with given travel demand and road network. It has long been criticized that travel times are inconsistent in the conventional four-step sequential model because travel times given in trip distribution are not consistent with those generated from traffic assignment. In fact, travel times are endogenously determined rather than exogenously provided. Generally

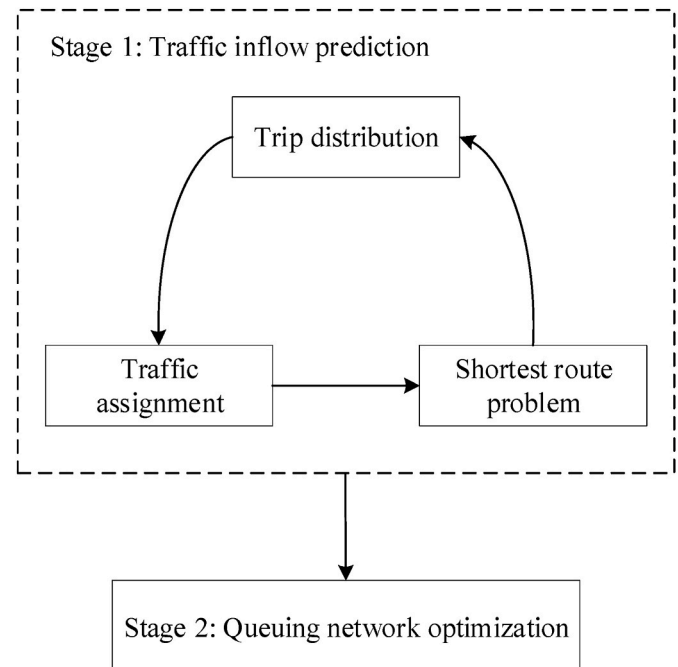


Fig. 2. The conceptual framework of the two-stage model.

speaking, two ways can be used to solve the inconsistent problem to achieve transportation system equilibrium in literature. One way is to combine several steps to equivalent mathematical programming, which can be proved to be a well-converged and consistent result [19,20]. The other is to provide feedback to the sequential models iteratively until travel times meet the consistency criteria [21,22]. Although the former is commonly adopted in literature, the latter is more flexible at each step [23,24]. Therefore, a combined model with feedback is adopted here.

More specifically, the first step model is conducted as follows, given travel demand and road network. Trip distribution is generated by aggregating individual destination choices. The multinomial logit (MNL) model is used for destination choices because it is regarded as the simplest and most practical. After the trip distribution matrix is generated, travel demands are inputted into the road network by user equilibrium to generate link traffic flows and link travel times. Then all of the OD pair travel times are produced by Dijkstra's algorithm. These travel times are fed back to the MNL model to update the trip distribution matrix. This process is iterated until the trip distribution matrix is well-converged. The state is known as the transportation system equilibrium. Finally, the traffic flows at each entrance link can be figured out. Fig. 3 illustrates the feedback process in the first stage model, where these notations are defined as follows.

- q_{rs} : travel demand between origin r and destination s ;
 - O_r : the travel demand in zone r ;
 - S_r : the set of destinations departed from origin r ;
 - β_s : traveler preference for destination s ;
 - t_{rs} : the path travel time between origin r and destination s ;
 - β_t : coefficient of travel time t_{rs} ;
 - v_a : traffic flow at link a ;
 - c_a : road capacity of link a ;
 - t_a : travel time at link a , which is a function of traffic flow v_a and road capacity c_a ;
 - f_k^{rs} : traffic flow on path k connecting origin r and destination s ;
 - $\delta_{a,k}^{rs}$: link-path incidence relationship, which is expressed as:
- $$\delta_{a,k}^{rs} = \begin{cases} 1, & \text{if link } a \text{ is on path } k \text{ connecting } r \text{ and } s \\ 0, & \text{if not} \end{cases}$$

2.2. Stage 2: Queuing network design

Queuing theory is an excellent tool to analyze the cost of waiting experienced by vehicles at each entrance link. In most traffic situations, interarrival and service times are described randomly by the exponential distribution. This stage adopts a general queuing model that combines both arrivals and services based on the Poisson assumptions. That is, the interarrival and the service times follow the exponential distribution. The derivation of the queuing model is based on the steady-state

behavior of the queuing situation, achieved after the system has been in operation sufficiently long.

According to the conventional traffic flow theory [25], the waiting line at each service station can be formulated as a fundamental $M/M/c$ queuing model, where M means Markovian (or Poisson) arrivals or departures distribution, or equivalently exponential interarrival or service time distribution, and c means the number of identical parallel servers with same service rate per unit time. There could be one or more parallel test stations (i.e., servers) at each entrance link. Suppose that there are m entrances at a sanitary cordon. It is necessary to study the entire queuing network performance. Assume that vehicles arrive at entrance i ($i = 1, 2, \dots, m$) according to a Poisson process with predicted inflow λ_i at the first stage and that entrance i has an exponential service time distribution with an identical parameter μ for its c_i parallel test stations, where $c_i\mu > \lambda_i$. Therefore, the elementary $M/M/c$ queuing model can be used to analyze each entrance independently of the others. It is better to use the $M/M/c$ model to obtain all performance measures for each entrance independently, rather than analyzing interactions between entrances, as it is usually difficult for vehicles to change entrances.

Analogous to a single service facility, the most commonly used measures of the queuing situation at a given entrance i are the expected number of customers in the queue (L_{q_i}) and expected waiting time in the queue (W_{q_i}). The relationship between L_{q_i} and W_{q_i} is known as Little's formula, and it is given as $L_{q_i} = \lambda_i W_{q_i}$. The relationship is valid under rather general conditions. Let $\rho_i = \lambda_i/\mu$, the expression L_{q_i} can be determined as follows:

$$L_{q_i} = \frac{\rho_i^{c_i+1}}{(c_i - 1)!(c_i - \rho_i)^2} p_{0_i}, \forall i \quad (1)$$

$$p_{0_i} = \left[\sum_{n=0}^{c_i-1} \frac{\rho_i^n}{n!} + \frac{\rho_i^{c_i}}{(c_i - 1)!(c_i - \rho_i)} \right]^{-1}, \forall i \quad (2)$$

$$\frac{\rho_i}{c_i} < 1, \forall i \quad (3)$$

where p_{0_i} is the steady-state probability of no customers in entrance i , and Eq. (3) is a steady-state condition. The measure W_{q_i} is determined by dividing L_{q_i} by λ_i according to Little's formula.

The queuing results can be incorporated into a cost-minimization model that seeks to minimize the sum of the cost of offering test stations and the cost of waiting time. It is straightforward that the service cost increases with the level of service (i.e., the number of test stations). At the same time, the waiting time decreases with the increase in the level of service. The cost-based model attempts to balance two conflicting costs: the cost of offering the service and vehicle waiting time. An increase in one cost automatically causes a decrease in the other. As the waiting time cost is difficult to be determined in dollars, it is adopted

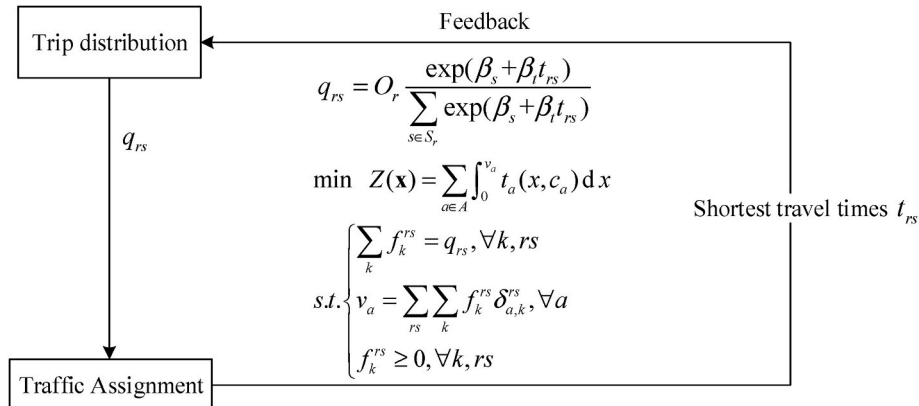


Fig. 3. The iterative process in the first step model.

as the desired constraint, while the cost of offering test stations is used as an objective. Therefore, the objective function can be expressed as

$$\text{MinEOC} = \sum_{i=1}^m c' c_i \quad (4)$$

where EOC is the expected cost of operating the facilities per unit time and c' is the marginal cost per test station per unit time. The expected total cost in the entire system is obtained by merely summing the corresponding quantities obtained at the respective entrances.

An acceptable disease control policy should consider queuing time constraints. The aspiration level model works directly with the performance measures of the queuing situation. The idea is to determine an acceptable range for the service level by specifying reasonable limits on performance measures. Such limits are the aspiration levels the decision-maker wishes to reach. Note that the service level in a given entrance i is a function of the number of parallel test stations c_i . This stage presents a decision model for determining acceptable service levels considering the average waiting time W_{qi} . The model recognizes that higher service levels reduce the waiting time in the system. The goal is to strike a balance between service level and waiting time. The problem reduces to determining the number of servers c_i such that

$$W_{qi} \leq T, \forall i$$

The constant T is the level of aspiration specified by the decision-maker; for example, $T = 3$ min. Note that W_{qi} is a function of c_i . According to Little's formula and Eqs. (1) and (2), the average waiting time W_{qi} can be specified more specifically as

$$W_{qi}(c_i) = \frac{\rho_i^{c_i+1}}{\lambda_i(c_i-1)!(c_i-\rho_i)^2} \left[\sum_{n=0}^{c_i-1} \frac{\rho_i^n}{n!} + \frac{\rho_i^{c_i}}{(c_i-1)!(c_i-\rho_i)} \right]^{-1} \leq T, \forall i \quad (5)$$

In conclusion, an integer nonlinear programming model can be proposed where the objective is to minimize the expected total cost of service operation, the constraint is an aspiration level of the vehicle waiting time at each entrance, and the decision variables are the number of parallel test stations at each entrance. It is formulated as

$$\text{MinEOC} = \sum_{i=1}^m c' c_i \quad (6)$$

$$\text{s.t.} \frac{\rho_i^{c_i+1}}{\lambda_i(c_i-1)!(c_i-\rho_i)^2} \left[\sum_{n=0}^{c_i-1} \frac{\rho_i^n}{n!} + \frac{\rho_i^{c_i}}{(c_i-1)!(c_i-\rho_i)} \right]^{-1} \leq T, \forall i \quad (7)$$

$$\frac{\rho_i}{c_i} < 1, \forall i \quad (8)$$

$$c_i \leq c'_i, \forall i \quad (9)$$

$$c_i \geq 0 \text{ and integer}, \forall i \quad (10)$$

The objective function in Eq. (6) is to minimize the expected total cost of test stations. Eq. (7) is the aspiration level of the vehicle waiting time for each entrance, where T is a constant determined by the policymaker. Eq. (8) is the steady-state condition. Eq. (9) enforces that the number of test stations c_i is not more than the physical capacity c'_i for each entrance. Eq. (10) makes sure that the decision variables are nonnegative integers. It should be noted that the integer nonlinear programming model is hard to solve, so a heuristic algorithm is designed in the following section.

3. Solution algorithm

3.1. Stage 1: The Method of Successive Averages

The traffic inflows predicted in the first stage model go into the second stage model as arrival rates. To solve the proposed two-stage

model, it is always beneficial to solve the first-stage model first. With a fixed travel demand and a built road network, there will be a stable flow pattern from the first stage. Note that there is a feedback procedure between trip distribution and traffic assignment. The Method of Successive Averages (MSA) can be used to achieve system equilibrium. An initial trip distribution matrix can be produced by an MNL model with initialized Origin-Destination (OD) pair travel times. The trips are then assigned to the road network by the Frank-Wolfe algorithm. The link travel flows and link travel times can be generated. According to Wardrop's first principle of route choice, also known as user equilibrium, traffic arranges itself in congested networks such that all used paths between an OD pair have an equal and minimum cost. Therefore, Dijkstra's algorithm is used to update OD pair travel times. These times are then fed back to the MNL model to generate a new trip distribution matrix. However, this matrix cannot be assigned to the road network directly. The convergence of direct or naive feedback is usually impossible. An averaging of successive trip distribution matrix is necessary. Although there are some successful applications of constant weights, convergence is usually not guaranteed. Therefore, the MSA with decreasing weight is used here to update the trip distribution matrix, which is the reciprocal of the iteration number. The updated matrix is further assigned to the road network. The iteration process continues until the successive matrices are quasi-equal. The convergence is generally measured by the squared root of the relative gap. If a predetermined tolerance is achieved, terminate the iteration. The stable state is known as the transportation system equilibrium. The resultant traffic inflows at all entrance links then go into the second stage model. Fig. 4 shows the flowchart of the first-stage algorithm.

The detailed MSA algorithm is specified step by step as follows.

Step 1 Input a fixed travel demand and a built road network.

Step 2 Initialize trip distribution matrix q_{rs}^0 with initial OD pair travel time t_{rs}^0 . Besides, let $n = 1$ be the number of iterations.

Step 3 Traffic assignment. The trip distribution matrix q_{rs}^0 is assigned to the road network by the Frank-Wolfe algorithm. The link travel flows v_a and link travel times t_a are generated.

Step 4 Update the shortest path travel time between an OD pair rs , namely t_{rs}^1 , by Dijkstra's algorithm.

Step 5 Trip distribution. The MNL model is used to update the trip distribution matrix q_{rs}^1 :

$$q_{rs}^1 = O_r \frac{\exp(\beta_s + \beta_t t_{rs}^1)}{\sum_{s \in S_r} \exp(\beta_s + \beta_t t_{rs}^1)} \quad (11)$$

Step 6 Average trip distribution matrices q_{rs}^1 and q_{rs}^0 using decreasing weight

$$q_{rs}^1 = q_{rs}^0 + \frac{1}{n} (q_{rs}^1 - q_{rs}^0) \quad (12)$$

Step 7 Convergence judgment. Check the convergence of the trip distribution matrix using the squared root of the relative gap:

$$\sqrt{\sum_{rs} \left(\frac{q_{rs}^1 - q_{rs}^0}{q_{rs}^0} \right)^2} < \varepsilon \quad (13)$$

where ε is a predetermined tolerance. If the convergence condition is satisfied, terminate the iteration and turn to Step 9; otherwise, turn to Step 8.

Step 8 Let $q_{rs}^0 := q_{rs}^1$ and $n := n + 1$. Then turn to Step 3.

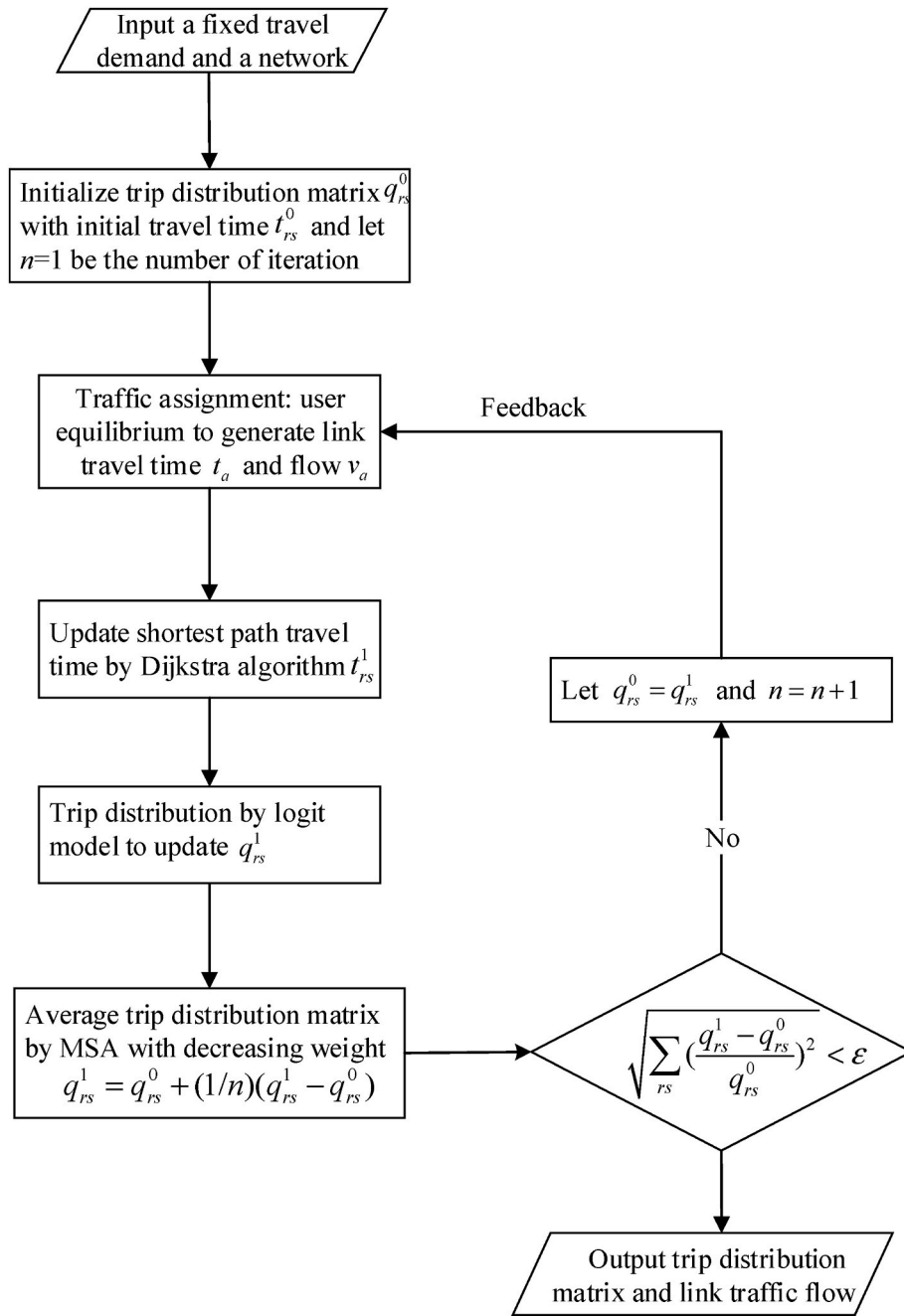


Fig. 4. The flowchart of the MSA algorithm.

Step 9 The outputs are the trip distribution matrix q_{rs}^1 and the link traffic flow v_a .

3.2. Stage 2: Genetic Algorithm with elite strategy

The traditional gradient-based exact algorithms to solve the integer nonlinear programming problems usually fail to converge for larger-scale problems due to multiple local optima. This failure led to the development of heuristic algorithms that are commonly used to generate high-quality solutions to complex optimization and search problems [26,27]. The heuristic algorithm was shown to successfully solve the cordon toll optimization problem, although it is found to be time-consuming, and there is no proof of convergence of the algorithm. However, the successful implications of heuristic methods, especially Genetic Algorithms, have been growing to generate high-quality cordon

schemes in the literature [12,28–30]. Therefore, a Genetic Algorithm with an elite strategy is also adopted here. Fig. 5 shows its flowchart.

The detailed Genetic Algorithm with an elite strategy is specified in steps as follows.

Step 1 Initialization. Set the parameters used in the Genetic Algorithm, including population size M , the maximum number of generations Gen , crossover probability p_c , mutation probability p_m , the notation of generation $gen = 1$, and the portion for elitist strategy p_e . Note that the population size depends on the nature of the problem but typically contains several hundreds of possible solutions.

Step 2 Generate a feasible initial population randomly. A chromosome is a solution that consists of m genes. Integer encoding technology is used where a gene stands for the number of parallel test stations at an entrance link. Generate a chromosome randomly. If it is

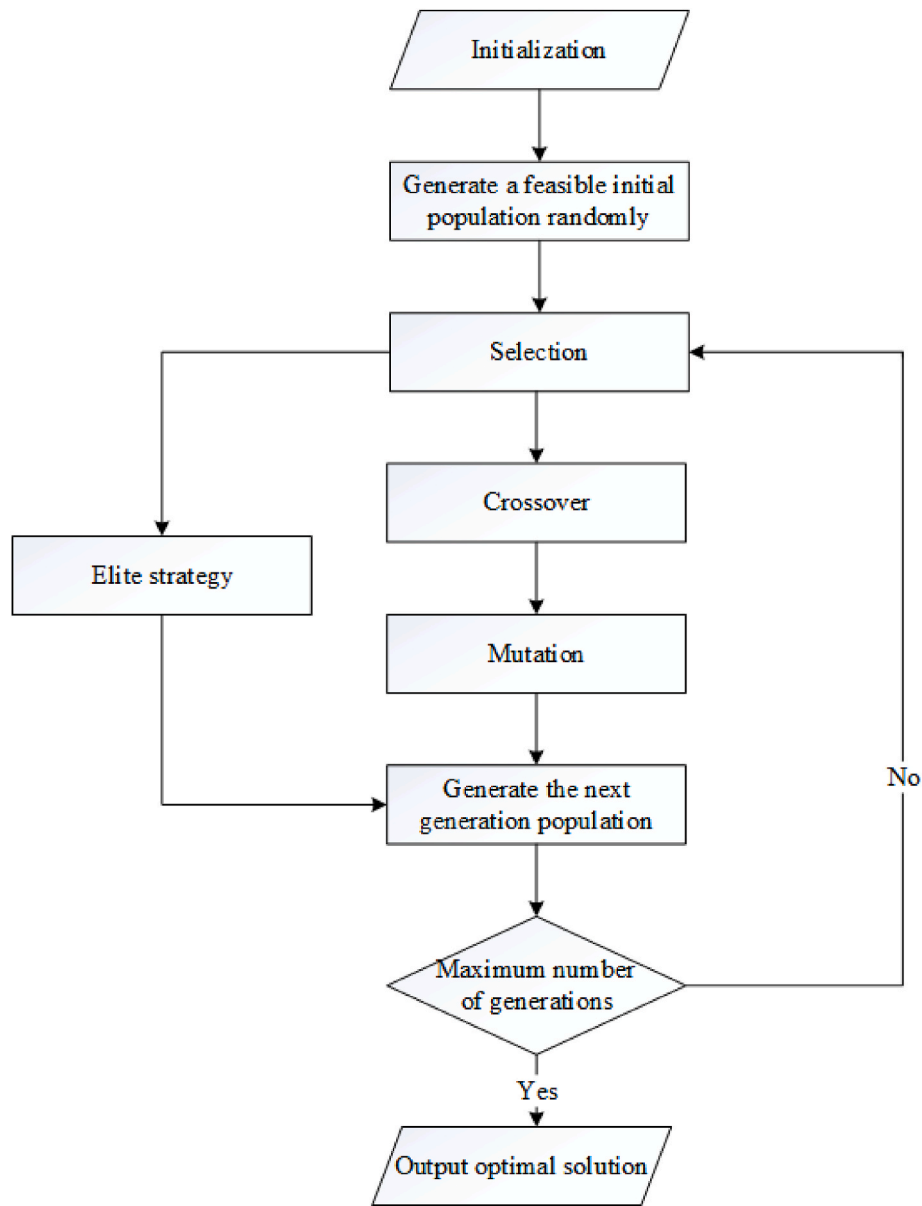


Fig. 5. The flowchart of the Genetic Algorithm with elite strategy.

not feasible, generate another one until it is achievable. A total number of M viable chromosomes are generated, scattering the entire range of possible solutions.

Step 3 Selection operation. The objective function of the second stage model is used to work as a fitness function to evaluate the performance of all chromosomes in the population. Note that it is to minimize the total number of test stations, the best p_e is labeled for elitists, and the worst p_e is discarded.

Step 4 Crossover operation. The remaining $(1 - p_e)M$ chromosomes are used for crossover operations. These parent chromosomes are matched in pairs randomly. The probability of carrying out the crossover is p_c . If it is chosen for the crossover, a random gene is identified. If newborn chromosomes are not feasible according to constraints in the second-stage model, try another gene location until they are achievable. These new solutions typically share many of the characteristics of their parents.

Step 5 Mutation operation. The probability of carrying out mutation is p_m . A random gene is identified for mutation within the domain of definition. If the new chromosome is not feasible, try another gene location until it is feasible.

Step 6 Generate the next generation population. After genetic operators, there are still $(1 - p_e)M$ feasible chromosomes. The labeled $p_e M$ elitists are added to ensure the population size M . This allows the best chromosomes from the current generation to carry over to the next unaltered. It guarantees that the solution quality will not decrease from one generation to the next. Let the notation of generation be $gen := gen + 1$.

Step 7 Termination judgment. If the maximum number of generations is achieved, that is $gen \geq Gen$, terminate the iteration process and output the optimal investment of cordon sanitaire. Otherwise, turn to Step 3.

4. Experimental study

An experimental study is conducted to verify the effectiveness of the proposed method and algorithm. The Nguyen-Dupuis road network, as shown in Fig. 6, is commonly used in transportation research to demonstrate various methods. There are 13 nodes and 19 links. The link characteristics, including free-flow travel time, link capacity, and link length, are shown in Table 1.

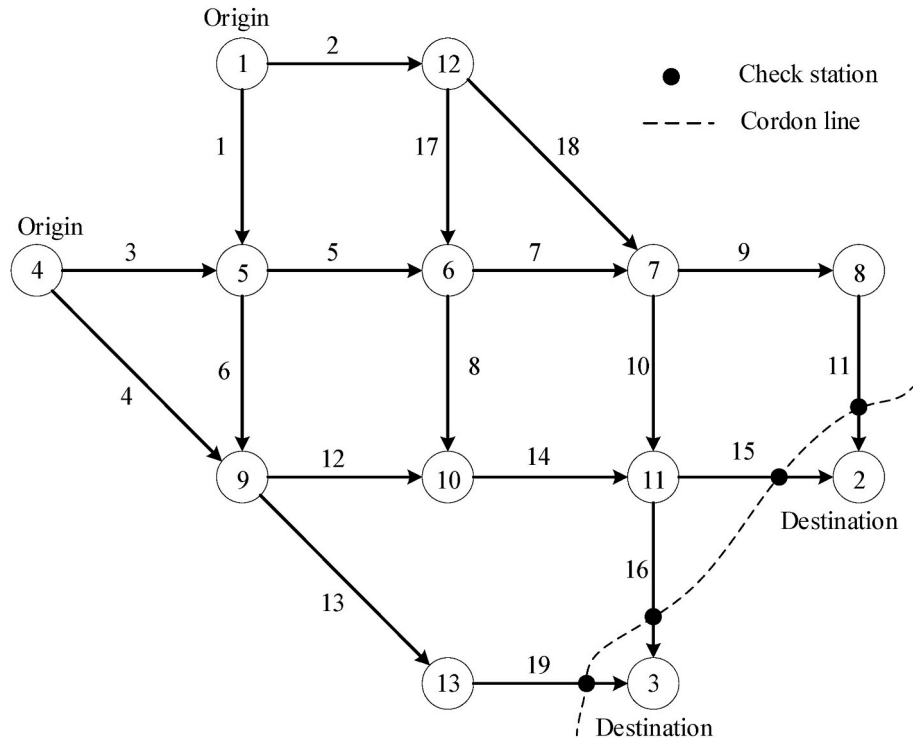


Fig. 6. The Nguyen-Dupuis road network.

Table 1
Link characteristics of the Nguyen-Dupuis road network.

Link a	Free flow time (min)	Link capacity (pcu/h)	Link length (km)
1	7.0	800	4.00
2	9.0	800	6.00
3	9.0	800	5.00
4	12.0	800	8.00
5	3.0	800	2.00
6	9.0	800	5.00
7	5.0	800	3.00
8	13.0	800	8.00
9	5.0	800	3.00
10	9.0	800	6.00
11	9.0	800	5.00
12	10.0	800	6.00
13	9.0	800	5.00
14	6.0	800	4.00
15	9.0	800	6.00
16	8.0	800	5.00
17	7.0	800	4.00
18	14.0	800	6.00
19	11.0	800	7.00

There are two origins and two destinations in the Nguyen-Dupuis network. The predicted travel demands at origin zones 1 and 4 are 1000 pcu/h and 1000 pcu/h, respectively. That is, $O_1 = 1000$ pcu/h and $O_4 = 1000$ pcu/h. All of the existing links are labeled from 1 to 19. The destination zones are 2 and 3, so the entrance links are 11, 15, 16, and 19. The problem is to determine the number of test stations at each entrance link to minimize the investment with a certain level of queuing time.

The parameters used in the first stage model are summarized as follows. The MNL model for destination choices is simplified as

$$q_{rs}^1 = O_r \frac{\exp(\beta_s + \beta_t t_{rs}^1)}{\sum_{s \in S_r} \exp(\beta_s + \beta_t t_{rs}^1)} \quad (14)$$

where β_s is traveler preference on destination s and β_t is the coefficient of

path travel time between O-D pair rs . The values of β_s and β_t can be calibrated empirically, which is out of this paper's scope. Here we set $\beta_2 = 0.5$, $\beta_3 = 0$, and $\beta_t = -0.1$. That is, the traveler's preference for destination zone 2 is 0.5, and for destination zone 3 is 0, which means that the travelers traditionally prefer destination 2. The coefficient of travel time is -0.1 , which means that the travel time is a negative utility. Besides, the well-known link impedance function, named BPR function, is used to accommodate the congestion effect in traffic assignment with the following formulation:

$$t_a(v_a, c_a) = t_a^0 \left[1 + \alpha \left(\frac{v_a}{c_a} \right)^\beta \right], a \in A \quad (15)$$

where t_a^0 is the free-flow travel time of link a ; α and β are volume/delay coefficients set as $\alpha = 0.15$ and $\beta = 1.5$ conventionally. The convergence criteria for MSA are set as $\varepsilon = 0.01$. A stable transportation system equilibrium can be achieved for a given road network.

The parameters used in the second stage model are listed as follows. The population size is $M = 500$. The maximum number of generations is $Gen = 20$. The portion for elitists is $p_e = 0.1$. The crossover probability is $p_c = 0.1$, and the mutation probability is $p_m = 0.5$. Although these parameters are conventionally used in Genetic Algorithms, it is worth tuning parameters to find appropriate settings for a specific problem. The allowed maximum waiting time at each entrance link is set as $T = 2$ min. The maximum number of test stations that can be set up at each entrance link is assumed to be $c_i' = 12, \forall i$. This is for simplicity, and they can be diverse. The marginal cost per station per unit time c' is set to be one without affecting the decision.

The predicted traffic volumes at entrance links from the first stage model work as the average arrival rates of the second stage model. Note that traffic volumes are usually measured in hours, while arrival rates are typically measured in minutes. Therefore, unit conversion is needed. The average service rate for a single station is assumed to be $\mu = 2$ pcu/min. That is, each station averagely tests two passenger car units per minute. The calculation is programmed using a popular open-source language, R 3.6.3, in a personal computer with Intel Core i7-4790

CPU @ 3.60 GHz. The running time is 3.97 s. The results are shown in Table 2.

It is shown that traffic inflow volumes are different at entrance links. The maximum one is 1013 *pcu/h* at entrance link 11, while the minimum one is only 110 *pcu/h* at entrance link 15. As a result, the number of test stations needed at each entrance link could not be even and will be different. The maximum number is 9, and the minimum number is 2. The total number of test stations is 20, which is the minimum investment cost to maintain the desired level of waiting (i.e., 2 min). In this way, the maximum waiting time at each entrance link will not exceed 2 min. However, attention should be paid to the issue of choosing the best parameters for the GA-based methods, i.e., generation number, population number, the probability of crossover, and the probability of mutation. They could affect computation time and accuracy.

5. Conclusions

The ongoing COVID-19 pandemic has caused global social and economic disruption. The urban cordon sanitaire is demonstrated to be an effective way to prevent or slow down the spreading of infectious diseases. However, some severe problems arise, such as the long waiting time for testing and the massive investment in test stations. This is a new resource allocation problem that has not been explored before.

This paper proposed a novel method to determine the minimum investment of deploying test stations at city entrances for the desired maximum queuing time. A two-stage optimization model is formulated where the first stage is traffic inflow prediction, and the second stage is queuing network design. The predicted traffic inflows from transportation system equilibrium go into a queuing model. The queuing theory is adopted to represent the waiting phenomenon at each entrance link. Then an integer nonlinear programming model is built where the objective is to minimize the total investment of test stations, and one of the constraints is to make the maximum waiting time within the desired level. A heuristic algorithm is proposed according to the two-stage decision structure. The Method of Successive Averages (MSA) is used to achieve a transportation system equilibrium in the first stage, and a Genetic Algorithm (GA) with an elite strategy is adopted to solve the integer nonlinear programming model in the second stage.

Several helpful findings are provided based on an experimental study. The well-known Nguyen-Dupuis road network is adopted to demonstrate the effectiveness of the proposed method and algorithm. Although the test is only limited to a simplified network, the results show that the proposed methods can find at least a useful optimal heuristic solution within a satisfactory time. It is helpful to make good use of scarce health resources for disease control and prevention purposes.

The limitations of this study imply suggestions for future works. First, the adopted Nguyen-Dupuis road network is a little bit simple. Undoubtedly, a large-scale network with realistic data will be more convincing. It is better to find a more realistic case to show how the methods can be applied in practice. Second, the variables and associated parameters used for traffic inflow prediction are not well established. There could be other variables affecting trip destination choices except for travel time, for example, parking convenience. The stochastic user equilibrium can also be used to substitute the deterministic user equilibrium model for traffic assignment, which could be more realistic. Third, the traditional Genetic Algorithm is used for algorithm design. Some other advanced heuristics are used for similar problems, such as the vibration damping optimization algorithm and cutting plane algorithm. We believe that these methods could be more efficient in computation. Comparing results across different heuristics in a table-item way with strengths and weaknesses would be interesting. Last but not least, an intelligent transportation system with traffic information in the context of digital economy can be used to redistribute test stations dynamically, which could be very helpful.

Table 2

The predicted traffic inflow volume and determined investment.

Entrance link	Traffic inflow volume (<i>pcu/h</i>)	Number of test stations
11	1013	9
15	110	2
16	382	4
19	495	5

Author contributions

Hongzhi Lin: Conceptualization, methodology, implementation, formal analysis, visualization, funding acquisition, writing - original draft. **Yongping Zhang:** Conceptualization, writing - draft editing, writing - review & editing.

Declaration of competing interest

None.

Data availability

The data used are included in the paper.

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References

- [1] Khan HUR, Usman B, Zaman K, Nassani AA, Haffar M, Muneer G. The impact of carbon pricing, climate financing, and financial literacy on COVID-19 cases: go-for-green healthcare policies. *Environ Sci Pollut Res* 2022;29:35884–96.
- [2] May AD, Liu R, Shepherd SP, Sumalee A. The impact of cordon design on the performance of road pricing schemes. *Transport Pol* 2002;9:209–20.
- [3] Verhoef ET. Second-best congestion pricing in general networks. Heuristic algorithms for finding second-best optimal toll levels and toll points. *Transp Res Part B Methodol* 2002;36:707–29.
- [4] Abulibdeh A, Andrey J, Melnik M. Insights into the fairness of cordon pricing based on origin-destination data. *J Transport Geogr* 2015;49:61–7.
- [5] Souche S, Mercier A, Ovtracht N. Income and access inequalities of a cordon pricing. *Res Transport Econ* 2015;51:20–30.
- [6] Souche S, Mercier A, Ovtracht N. The impacts of urban pricing on social and spatial inequalities: the case study of Lyon (France). *Urban Stud* 2016;53:373–99.
- [7] Camporeale R, Caggiani L, Fonzone A, Ottomanelli M. Study of the accessibility inequalities of cordon-based pricing strategies using a multimodal Theil index. *Transport Plann Technol* 2019;42:498–514.
- [8] Gühnemann A, Koh A, Shepherd S. Optimal charging strategies under conflicting objectives for the protection of sensitive areas: a case study of the trans-pennine corridor. *Network Spatial Econ* 2016;16:199–226.
- [9] Li X, Lv Y, Sun W, Zhou L. Cordon- or link-based pricing: environment-oriented toll design models development and application. *Sustainability* 2019;11.
- [10] Gupta S, Kalmanje S, Kockelman KM. Road pricing simulations: traffic, land use and welfare impacts for Austin, Texas. *Transport Plann Technol* 2006;29:1–23.
- [11] Rodriguez-Roman D, Ritchie SG. Surrogate-based optimization for the design of area charging schemes under environmental constraints. *Transport Res Transport Environ* 2019;72:162–86.
- [12] Liu Z, Meng Q, Wang S. Speed-based toll design for cordon-based congestion pricing scheme. *Transport Res C Emerg Technol* 2013;31:83–98.
- [13] Liu Z, Meng Q, Wang S. Variational inequality model for cordon-based congestion pricing under side constrained stochastic user equilibrium conditions. *Transportmetrica: Transport Sci* 2014;10:693–704.
- [14] Liu Z, Wang S, Meng Q. Optimal joint distance and time toll for cordon-based congestion pricing. *Transp Res Part B Methodol* 2014;69:81–97.
- [15] Afandizadeh S, Abdolmanafi SE. Cordon pricing considering air pollutants emission. *Promet - Traffic - Traffico* 2016;28:179–89.
- [16] Johari M, Haghshenas H. Modeling the cordon pricing policy for a multi-modal transportation system. *Case Stud Transp Policy* 2019;7:531–9.
- [17] Guo Q, Sun Y, Li ZC, Li Z. An integrated model for road capacity choice and cordon toll pricing. *Res Transport Econ* 2017;62:68–79.
- [18] Kono T, Kawaguchi H. Cordon pricing and land-use regulation. *Scand J Econ* 2017;119:405–34.
- [19] Sheffi Y. *Urban transportation networks*. Englewood Cliffs, NJ: Prentice-Hall; 1985.
- [20] Oppenheim N. *Urban travel demand modeling: from individual choices to general equilibrium*. John Wiley and Sons; 1995.

- [21] Boyce DE, Zhang Y-F, Lupa MR. Introducing“ feedback” into four-step travel forecasting procedure versus equilibrium solution of combined model. *Transport Res Rec* 1994;1443:65–74.
 - [22] Boyce D, Zhang Y-F. Calibrating combined model of trip distribution, modal split, and traffic assignment. *Transport Res Rec* 1997;1607:1–5.
 - [23] Lin H. An accessibility-oriented optimal control method for land use development. *J Urban Plann Dev* 2019;145:04019011.
 - [24] Lin H-Z, Wei J. Optimal transport network design for both traffic safety and risk equity considerations. *J Clean Prod* 2019;218:738–45.
 - [25] Gartner NH, Messer CJ, Rathi A. Revised monograph on traffic flow theory. United States: Federal Highway Administration; 1999.
 - [26] Babaeinesami A, Tohidi H, Ghasemi P, Goodarzian F, Tirkolaee EB. A closed-loop supply chain configuration considering environmental impacts: a self-adaptive NSGA-II algorithm. *Appl Intell* 2022;52:13478–96.
 - [27] Safaei S, Ghasemi P, Goodarzian F, Momenitabar M. Designing a new multi-echelon multi-period closed-loop supply chain network by forecasting demand using time series model: a genetic algorithm. *Environ Sci Pollut Res* 2022;29:79754–7976.
 - [28] Shepherd S, Sumalee A. A genetic algorithm based approach to optimal toll level and location problems. *Network Spatial Econ* 2004;4:161–79.
 - [29] Sumalee A. Optimal road user charging cordon design: a heuristic optimization approach. *Comput Aided Civ Infrastruct Eng* 2004;19:377–92.
 - [30] Sumalee A. Multi-concentric optimal charging cordon design. *Transportmetrica* 2007;3:41–71.
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